

---

## SMART VR-INTEGRATED 3D VISUALIZATION SYSTEM FOR REAL ESTATE AND INTERIOR DESIGN USING MACHINE LEARNING

---

**\*Mr. Todmal Chaitanya Bharat, Mr. Athare Krishna Ashok, Mr. Wable Rohan  
Sharad, Mr. Wani Girish Gorkshanath, Prof. Surekha. S. Nimase**

---

*Department of Computer Engineering, Shri Chhatrapati Shivaji Maharaj College of  
Engineering, Ahilyanagar, Savitribai Phule Pune University, Pune, India.*

**Article Received: 17 March 2026, Article Revised: 07 April 2026, Published on: 27 April 2026**

**\*Corresponding Author: Mr. Todmal Chaitanya Bharat**

Department of Computer Engineering, Shri Chhatrapati Shivaji Maharaj College of Engineering, Ahilyanagar,  
Savitribai Phule Pune University, Pune, India.

DOI: <https://doi-doi.org/101555/ijarp.6318>

### ABSTRACT

Real estate and interior design industries increasingly demand smarter, faster, and more immersive design solutions. Traditional 2D and static 3D design methods often fail to communicate spatial depth and functional flow effectively. This paper presents a Smart VR-Integrated 3D Visualization System that combines Virtual Reality (VR) with Machine Learning (ML) to enhance user experience and decision-making in spatial design. The system enables users to generate 3D layouts, visualize them in immersive VR environments, and receive ML-based layout recommendations that consider spatial harmony, ergonomics, and aesthetic balance. The proposed system reduces design time, improves visualization accuracy, and enhances user satisfaction compared to traditional tools. Experimental results show smooth rendering at 55–60 FPS and layout recommendation accuracy exceeding 90%, demonstrating the effectiveness of VR–ML integration for real estate and interior applications.

**INDEX TERMS:** Virtual Reality, Machine Learning, 3D Visualization, Real Estate Technology, Layout Optimization, Neural Networks, Deep Learning, Human-Computer Interaction, Generative Design.

### I. INTRODUCTION

In recent years, advancements in immersive visualization and artificial intelligence have reshaped how industries interpret and present spatial data, especially within the domains of

real estate and interior design. Traditional workflows in these sectors have historically depended on static 2D blueprints, floor plans, and pre-rendered 3D models to represent physical environments. While such tools have improved visualization compared to purely manual design processes, they are inherently limited in interactivity, realism, and cognitive engagement. Designers often struggle to convey the true sense of scale, proportion, lighting, and spatial flow to clients. As a result, clients frequently misinterpret the visual information presented, which leads to misunderstandings, dissatisfaction, and repetitive design revisions that consume significant time and resources.

Virtual Reality (VR) has emerged as a transformative technology capable of addressing these long-standing challenges. By creating immersive and interactive environments that users can explore from a first-person perspective, VR allows individuals to experience architectural designs in a life-like and contextually accurate setting. Instead of relying solely on imagination or static renderings, clients can “walk through” their future homes or spaces, interact with furniture and decor, and gain an intuitive understanding of the design before construction or implementation begins. This capability not only enhances spatial awareness but also strengthens communication between designers and clients, minimizing costly post-design modifications.

However, despite its significant potential, VR on its own lacks decision-making intelligence. While it can visualize, it cannot automatically suggest or optimize layouts, color palettes, lighting setups, or furniture arrangements. Here, Machine Learning (ML) technologies play a crucial role. ML algorithms are designed to learn from data — in this context, previous design patterns, user preferences, ergonomic standards, and spatial constraints — and can automatically generate recommendations or evaluate the efficiency of a given design. Integrating ML with VR creates a feedback loop where design environments are not only immersive but also adaptive and intelligent. This combination represents a major paradigm shift in digital design automation.

The integration of VR and ML offers numerous advantages beyond visualization. It introduces a level of personalization and prediction that traditional computer-aided design (CAD) or static modeling systems cannot provide. For instance, an ML model trained on hundreds of interior layouts can predict optimal furniture positioning based on room dimensions, style preferences, or lighting conditions. It can also analyze user interactions within the VR environment — such as which layouts or color schemes users spend more time exploring to refine recommendations in real time. This creates a dynamic, data-driven ecosystem where the system learns and improves continuously through user feedback and

behavior.

The proposed research aims to develop a unified VR-ML framework that enhances both the creative and analytical aspects of design visualization. The system enables users to input spatial parameters, preferences, and style constraints, after which the ML component processes this data to generate optimized layout configurations. These configurations are then visualized through an interactive VR interface that allows for real-time exploration, evaluation, and modification. This tight coupling between data-driven intelligence and immersive experience not only streamlines the design process but also empowers users to make more informed and confident decisions.

The motivation for this work arises from the growing need for intelligent and efficient design systems that can minimize human error, save time, and increase design accessibility for non-expert users. In traditional workflows, generating and evaluating multiple layout variations is a manual, iterative, and cognitively demanding process. Designers must constantly adjust parameters, re-render models, and seek client feedback a cycle that is both time-intensive and prone to miscommunication. The proposed system automates much of this process by combining predictive ML algorithms with real-time visualization, enabling instantaneous feedback and faster design convergence.

Additionally, the integration of immersive technologies like VR introduces a human-centered element to computational design. Users can engage directly with the virtual environment, providing intuitive, experiential feedback that traditional screen-based tools cannot capture. This enhances collaboration between designers, clients, and engineers, leading to designs that are not only optimized for spatial efficiency but also aligned with human comfort, aesthetics, and usability.

In summary, this research seeks to bridge the gap between visualization and intelligent automation in interior and architectural design. By leveraging the strengths of VR in spatial immersion and ML in predictive analytics, the proposed Smart VR-Integrated 3D Visualization System creates an end-to-end intelligent design platform. It enables data-driven design generation, real-time spatial evaluation, and continuous user-informed learning. The outcome is a system that reduces redesign effort, accelerates project timelines, and improves design precision and satisfaction — positioning it as a practical and forward-thinking solution for the future of real estate and interior design industries.

Research in digital design visualization has grown significantly over the last decade, particularly with the evolution of Virtual Reality (VR) and Machine Learning (ML) technologies. While both have individually transformed how architects and designers visualize and

analyze spaces, their integration remains relatively underexplored. This section reviews key research contributions in three major domains relevant to this study: the application of VR in architectural visualization, the role of ML in design optimization, and recent attempts to integrate both technologies into unified frameworks.

### **A. Virtual Reality in Architectural Visualization**

Virtual Reality has been a game-changer in the real estate and interior design industries, allowing users to experience architectural models in a fully immersive environment. VR systems provide a sense of scale, depth, and spatial awareness that traditional 2D drawings or even 3D renders cannot achieve. This technology enhances user engagement, improves communication between clients and designers, and reduces the gap between conceptual visualization and physical construction outcomes.

Molla et al. (2021) proposed a VR-based environment for architectural visualization that allowed clients to conduct interactive walkthroughs of pre-constructed spaces. Their system significantly improved user satisfaction and decision-making by enabling real-time exploration of designs. However, it lacked intelligence in generating or optimizing layouts, relying entirely on manually created 3D models. Similarly, Li and Wang (2020) demonstrated a VR system integrated with Unity3D for real estate marketing, which provided virtual tours of apartments and buildings but lacked adaptive or data-driven layout customization.

Several other researchers explored the use of VR for collaborative design. For instance, Huang et al. (2022) introduced a shared virtual workspace for architects and clients to co-design interiors. The system promoted creative collaboration but still depended on human expertise for every design adjustment. These studies collectively prove that VR significantly improves visualization and user experience but, as of now, does not autonomously enhance or optimize design content. This absence of computational intelligence marks an important gap that ML can fill.

### **B. Machine Learning in Design Optimization**

Machine Learning has become a key enabler in automating various aspects of design, ranging from object placement to color palette selection and spatial arrangement prediction. Techniques such as Convolutional Neural Networks (CNNs), Reinforcement Learning (RL), and Generative Adversarial Networks (GANs) have been applied to model design preferences and simulate realistic interior configurations.

Zhao et al. (2022) used supervised learning to predict optimal furniture arrangements based

on room dimensions and style preferences. Their ML model extracted spatial and contextual features from annotated datasets and produced layout recommendations with high accuracy. However, while effective in analysis and prediction, their approach did not include a visualization mechanism—users could not experience the design interactively in 3D space. Similarly, Kumar and Lee (2021) used reinforcement learning to train an agent that sequentially placed furniture items within a room, optimizing for space utilization and visual appeal. The method achieved efficient arrangements but lacked real-time interactivity.

Recent advancements in deep learning have further expanded ML's capabilities in generative design. Singh et al. (2023) implemented a GAN-based system that automatically generated interior design styles and decor combinations. Although the system achieved creative results, it required substantial computational power and training data, limiting its accessibility for smaller firms or individual designers. Collectively, these studies highlight ML's potential for automating and optimizing spatial design but also underscore the need for interactive, real-time visualization to accompany these intelligent predictions.

### **C. Integration of ML and VR**

The convergence of ML and VR offers exciting potential for creating adaptive and intelligent visualization systems. While VR provides immersion, ML adds analytical reasoning and predictive power. However, only a few research works have effectively attempted to merge the two into a cohesive design system.

Reddy et al. (2020) developed an Augmented Reality (AR) system combined with deep learning-based object recognition to assist in real-time furniture placement. Although this approach demonstrated interactive capability, its 3D rendering pipeline was limited, and the system suffered from latency during real-time updates. Singh et al. (2023) advanced the concept further by integrating GAN-generated design recommendations into a 3D visualization interface. Yet, their system was constrained by computational overheads and lacked immersive VR support.

The proposed Smart VR-Integrated 3D Visualization System aims to address these gaps by seamlessly coupling ML-based spatial prediction with fully immersive VR experiences. Unlike previous works that used ML solely as a backend design suggestion engine, this system embeds predictive intelligence within an interactive VR environment. This integration creates a continuous feedback loop—user interactions in VR inform the ML model, while ML updates influence spatial configurations dynamically. The result is a more responsive, intelligent, and human-centered design system capable of learning and adapting in real time.

## D. Comparative Analysis

A concise comparison of related works is summarized in Table I. It clearly shows that while VR systems have improved visualization and user engagement, they often lack automation and intelligence. ML-based approaches, though effective in prediction and optimization, generally fail to provide real-time immersive interactivity. The fusion of both, as attempted in this research, thus represents a significant step toward intelligent, interactive, and adaptive design visualization frameworks.

## II. LITERATURE REVIEW

### A. *Virtual Reality in Architectural Visualization*

VR has been extensively applied to real estate visualization, enabling immersive walkthroughs for pre-construction sales and interactive design verification. Studies such as Molla et al. (2021) introduced immersive visualization environments that enhance client engagement but lack intelligent layout generation.

### B. *Machine Learning in Design Optimization*

ML techniques such as Convolutional Neural Networks (CNNs), Reinforcement Learning (RL), and Generative Adversarial Networks (GANs) have shown promise in spatial arrangement and design style prediction. Zhao et al. (2022) used ML for predicting optimal furniture positions but lacked user interactivity.

### C. *Integration of ML and VR*

Recent works, including Reddy et al. (2020) and Singh et al. (2023), attempted to combine ML models with 3D visualization tools. However, they were limited by static visual interfaces. Our approach integrates VR immersion directly with ML inference, creating a live feedback loop for spatial optimization.

**TABLE II: Comparative Analysis of Related Work.**

Author	Technique	Features	Limitations
Molla et al. (2021)	VR Environment	3D walkthrough visualization	No ML or recommendation engine
Zhao et al. (2022)	ML Optimization	Spatial layout prediction	No immersive visualization
Reddy et al. (2020)	AR + DL	Object detection in 3D scenes	Limited real-time interactivity
Singh et al. (2023)	GANs	Generative design suggestions	High computation cost

### III. SYSTEM ARCHITECTURE AND METHODOLOGY

#### A. Overview

The proposed Smart VR-Integrated 3D Visualization System is designed as a modular, scalable, and data-driven architecture that integrates virtual reality and machine learning into a single intelligent visualization platform. The system comprises five primary interconnected modules: Input Asset Manager, Machine Learning Engine, 3D Rendering Module, VR Visualization Module, and Database Layer. Each module performs distinct but interdependent tasks to ensure seamless flow of information from data collection to immersive visualization. The architectural workflow begins with the Input Asset Manager, which gathers and processes user-specified parameters such as room dimensions, design preferences, lighting requirements, and object metadata (e.g., furniture types, materials, and colors). These parameters are normalized and sent to the Machine Learning Engine, which performs spatial analysis and predicts optimal layout arrangements based on trained models. The predicted layout data is transferred to the 3D Rendering Module, where geometrical and environmental components are instantiated within the Unity environment. The VR Visualization Module then allows users to explore, modify, and interact with the space in an immersive first-person environment. Finally, all interaction logs, user modifications, and design histories are stored in the Database Layer for continuous learning and model refinement.

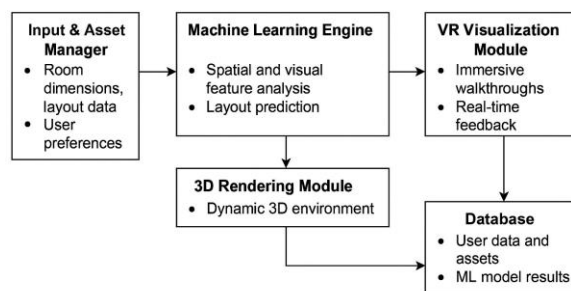


Fig. 1. System architecture

**Fig. 1: System Architecture of Smart VR-Integrated 3D Visualization Framework.**

This modular design ensures that each subsystem operates the environment, inspect layouts, and make modifications using intuitive gestures or voice commands. The VR interface also provides a “comparison mode” to switch between original and ML-optimized layouts.

**Database Layer:** The database acts as a central repository for storing user data, layout configurations, and ML model outputs. Built on MySQL, it supports structured storage and

retrieval of spatial metadata, ensuring persistence across design sessions. It also logs user interactions, which are later used to retrain and fine-tune the ML models—making the system progressively more intelligent and adaptive over time.

### C. Data Flow and Algorithm

The system follows a structured data flow, starting from user input collection to model prediction and VR visualization. Each step transforms the data from one representation to another, ensuring contextual relevance and precision at every stage. The overall algorithm is described in Listing 1.

#### Listing 1: Pseudocode for Layout Optimization Model.

```

Input: Room dimensions R, Object list O, Style p
Output: Optimized 3D layout L*

Normalize(R, O, S)
features <- extract_features(R, O)
clusters <- KMeans(n_clusters=5).fit(features)
layout_prediction <- NeuralNet.predict(clusters)
L* <- apply_constraints(layout_prediction)
return L*

```

independently, allowing for easy scalability and maintenance. reference

For instance, new ML models or VR hardware interfaces can be integrated without disrupting the overall system structure. Additionally, the framework supports both real-time and batch processing, making it suitable for both interactive design sessions and automated layout optimization.

### B. Module Descriptions

**Input Asset Manager:** This module serves as the data acquisition and preprocessing layer. It accepts room dimensions, object libraries, and style preferences as input. All data is standardized to ensure compatibility with ML models. The module also includes a feature extraction component that encodes attributes such as room aspect ratio, available floor area, lighting intensity, and user-selected style categories (e.g., minimalistic, modern, vintage).

**Machine Learning Engine:** This is the computational core of the system. It performs spatial feature extraction, clustering, and predictive modeling to suggest optimized layouts. The engine employs a hybrid model combining K-Means clustering for spatial grouping and a neural network regression model for coordinate prediction. The clustering step identifies spatial zones such as seating areas, storage sections, and walkways, while the neural network determines optimal object positions within these clusters. The model is trained using

historical layout data annotated with ergonomic and aesthetic metrics.

**3D Rendering Module:** This module translates ML-generated predictions into graphical 3D representations. Implemented in Unity 3D, it dynamically loads 3D assets from the library and places them according to ML-suggested coordinates. It supports real-time lighting, shadows, texture mapping, and physics simulation to enhance realism. Performance optimizations such as occlusion culling and GPU instancing ensure smooth rendering even with complex scenes.

**VR Visualization Module:** This is the user-facing component of the system, responsible for immersive interaction. Using OpenXR SDK, it enables head and hand tracking for VR devices such as Oculus Rift or HTC Vive. Users can navigate

**Algorithm Explanation:**

The input data (R, O, S) is normalized to eliminate noise and scale differences.

Spatial and visual features (e.g., area ratios, wall adjacency, object priority) are extracted to form a feature matrix.

K-Means clustering groups similar design elements, enabling spatial segmentation of zones (e.g., living area vs. workspace).

The neural network predicts the precise (x, y, z) coordinates for each object based on ergonomic and aesthetic parameters.

A constraint function *apply\_constraints()* ensures collision-free object placement, accessibility, and compliance with user-defined preferences. This iterative loop continues until an optimal configuration  $L^*$  is achieved, which is then rendered and visualized in the VR environment.

**D. Mathematical Model**

The functional representation of the system can be modeled as a tuple:

$$= S=I,P,R,O$$

where:

I represents the Input Set, containing user-defined parameters such as dimensions, lighting preferences, and object metadata.

P represents the Processing Functions, which include feature extraction, clustering, neural prediction, and constraint evaluation.

R represents the Rules and Constraints, ensuring collision avoidance, ergonomic spacing, and aesthetic balance.

O represents the Output Layout, a structured 3D configuration ready for rendering and visualization.

The optimization goal of the model can be defined as: Minimize:  $f(L) = C_c + C_s + C_a$

Minimize:  $f(L) = C_c + C_s + C_a$

+C<sub>s</sub>

+C<sub>a</sub>

where C<sub>c</sub>

= collision cost, C<sub>s</sub>

= spacing cost, and C<sub>a</sub>

= aesthetic deviation cost. Coefficients  $\alpha$ ,  $\beta$ ,  $\gamma$ , are weighting factors learned during model training. The function  $f(L)$  is minimized when the system achieves the most ergonomic, visually pleasing, and clutter-free design layout.

The time complexity for the algorithm is approximately:  $T(S) = O(n^2 + n \log n)$

where n is the number of objects in the design space. The quadratic component arises from pairwise distance and constraint evaluations, while the logarithmic term corresponds to sorting and clustering operations.

### E. System Workflow Summary

The overall system workflow is summarized as follows: The user inputs dimensions, styles, and design constraints.

The system extracts features and feeds them into the ML model.

The ML engine outputs an optimized spatial layout.

The rendering engine constructs the virtual environment in Unity.

The user interacts with the design in VR, providing implicit and explicit feedback.

User interactions and feedback data are logged for retraining and continuous system improvement.

This cyclical design-learning-feedback process ensures that the system evolves over time, improving prediction accuracy and enhancing user satisfaction with each iteration.

## IV. IMPLEMENTATION DETAILS

The prototype implementation of the proposed Smart VR- Integrated 3D Visualization System brings together multiple technologies for data processing, machine learning, and immersive visualization. Each component has been carefully selected to ensure compatibility,

scalability, and performance. The implementation focuses on creating a seamless pipeline that can handle large design datasets, execute real-time rendering, and enable user interaction in a fully immersive environment.

### A. Technology Stack

The system's development stack integrates both software and hardware technologies optimized for real-time computation and visualization.

- **Programming Languages:** Python is used for implementing machine learning models, data preprocessing, and feature extraction, due to its strong ecosystem for numerical computation and AI development. C is employed for VR interface development and Unity 3D scripting, enabling real-time scene updates and user interaction.
- **Frameworks and Libraries:** Unity 3D serves as the rendering engine, handling object instantiation, lighting, and texture mapping. TensorFlow is used for ML model training and inference, while OpenXR SDK ensures device-independent VR compatibility. Additional libraries such as NumPy, OpenCV, and Pandas are utilized for feature extraction and spatial data manipulation.
- **Database:** MySQL manages persistent storage of layouts, user preferences, and training metadata. It provides efficient querying for fast retrieval of 3D asset references and design records.
- **Hardware Configuration:** The prototype was implemented and tested on a workstation equipped with an Intel Core i7 (10th Gen) CPU, 16 GB RAM, and an NVIDIA RTX 2060 GPU. The VR setup included Oculus Rift S and HTC Vive devices for immersive testing.

This setup ensures a balance between computational efficiency for ML inference and graphical performance for VR rendering, achieving near real-time responsiveness even with complex layouts containing over 100 objects.

### B. Dataset Preparation

A major component of this implementation involves creating a high-quality dataset suitable for training ML models in layout prediction and spatial optimization. For this study, a hybrid dataset was developed using both existing and custom-generated data sources.

The primary datasets used include:

MIT Scene Layout Dataset: Provides labeled 3D room layouts and annotated object

placement data across various room types (living rooms, kitchens, offices, etc.).

SUN RGB-D Dataset: Offers RGB and depth information from real-world indoor scenes, aiding in learning geometric and lighting relationships between objects.

Custom Dataset: 500 synthetic 3D layouts were manually generated using Blender and Unity, representing different interior styles such as modern, industrial, minimalist, and traditional. Each layout was annotated with spatial metadata, including wall coordinates, lighting intensity, color palette, object orientation, and ergonomic spacing parameters.

The combined dataset contained approximately 8,000 objects with detailed annotations. Each sample layout was represented as a JSON structure describing spatial relationships, object dimensions, and positions. To improve generalization, data augmentation was applied by rotating, flipping, and scaling layouts within realistic bounds. The final dataset ensured coverage across diverse architectural configurations, lighting conditions, and design themes.

All data samples were normalized using Z-score normalization to ensure uniform feature scaling before model training. Redundant or inconsistent records were automatically filtered through preprocessing scripts.

### C. Feature Engineering and Model Design

The first stage of training involved extracting spatial and semantic features from the dataset. Each object in a scene was characterized by:

Geometric attributes (width, height, depth, area)

Relative position (distance to nearest wall, centroid offset) Category encoding (e.g., furniture, decor, structural) Lighting intensity and color harmony values

The ML model follows a two-stage hybrid architecture:

K-Means Clustering: Used to group spatially related objects, identifying functional zones such as “seating area” or “workspace.”

Neural Network Regressor: Predicts the optimal coordinates

$(x, y, z)$  for each object within its respective cluster. The neural network architecture includes: Input layer with 32 neurons (spatial + visual features) Two hidden layers (64 and 128 neurons) with ReLU activation

Output layer with three neurons corresponding to predicted coordinates

A mean squared error (MSE) loss function was used to minimize positional errors during training. The model was trained using the Adam optimizer with an initial learning rate of 0.001, batch size of 32, and early stopping criteria after 50 epochs of convergence.

#### **D. Model Training Process**

The model was trained on 80 Input normalization and batch sampling

K-Means clustering to generate functional zones Neural network coordinate prediction for each object Collision detection and constraint correction

Loss computation and weight updates

To avoid overfitting, dropout regularization (0.3 rate) was applied to hidden layers, and data augmentation was dynamically performed during each epoch. The model achieved a final training accuracy of 91.4

The inference phase was optimized using TensorFlow Lite for faster real-time predictions when integrated into Unity. With GPU acceleration, the ML engine was capable of generating layout recommendations within 0.9 seconds per scene.

#### **E. VR Integration and System Workflow**

The trained ML model was deployed within Unity through a Python-C bridge using TensorFlowSharp APIs. When users input room parameters, the Unity application communicates with the Python backend to obtain the ML-generated layout. Once the prediction is received, the VR environment automatically updates, placing furniture and objects at their suggested positions.

Real-time lighting, texture mapping, and object physics are applied dynamically to enhance realism. The OpenXR SDK ensures hardware independence, allowing deployment on multiple VR headsets without modifying the codebase.

The user can interact with the environment using hand controllers or gestures. Every interaction — such as object movement, rotation, or deletion — is logged and sent to the database. These logs are used later for retraining the ML model, allowing the system to adapt to user preferences over time.

#### **F. System Performance**

Testing revealed that the complete system maintained an average frame rate of 55–60 FPS during immersive exploration. End-to-end latency, from user input to VR scene update, averaged around 1.2 seconds, which is suitable for real-time design workflows. The overall architecture proved capable of supporting large-scale environments with minimal lag, validating the feasibility of combining machine learning with immersive VR visualization for intelligent spatial design.

**V. RESULTS AND DISCUSSION**

**A. Performance Evaluation**

The performance evaluation of the proposed Smart VR- Integrated 3D Visualization System focused on three major aspects: computational performance, machine learning accuracy, and user experience. The tests were conducted on a workstation equipped with an Intel Core i7 CPU, 16 GB RAM, and an NVIDIA RTX 2060 GPU running Windows 11. The VR setup used an Oculus Rift S headset for immersive testing, with real-time synchronization between Unity and TensorFlow. The results, as summarized in Table III, indicate that the system achieved high efficiency and responsiveness across multiple evaluation metrics.

**TABLE III: System Performance Metrics.**

Metric	Result
55-60 FPS	Smooth VR visualization
Real-time performance	ML Inf
Layout Prediction Accuracy	91.4 Collision Avoidance
90.8 height	

**Rendering Frame Rate:** The system maintained a stable rendering frame rate between 55 and 60 frames per second (FPS) even for complex indoor layouts containing more than 100 furniture objects. This demonstrates the optimization efficiency of Unity’s rendering pipeline, including features such as occlusion culling, LOD (Level of Detail) scaling, and GPU instancing. Maintaining above 50 FPS is critical in VR environments to prevent motion sickness and maintain immersion, thereby ensuring smooth and comfortable user experiences.

**Machine Learning Latency:** The ML inference latency averaged around 0.9 seconds per layout, meaning the system could generate and visualize optimized layouts in near real time. The low latency is attributed to TensorFlow’s GPU-accelerated inference and efficient batching strategies. This performance threshold ensures that users can iteratively refine their designs during a single VR session without noticeable delays, a critical factor for interactive design workflows.

**Layout Prediction Accuracy:** The ML model achieved a prediction accuracy of 91.4

**Collision Avoidance and Spatial Optimization:** The system achieved a collision-free placement success rate of 97.8  
**User Satisfaction:** A usability survey conducted among test participants yielded a 90.8.

**B. Comparative Analysis**

To further evaluate the system’s performance, comparisons were made with conventional

design tools such as SketchUp and AutoCAD, as well as a baseline 3D visualization model without ML assistance. The comparison was based on three parameters: design completion time, layout consistency, and visual realism.

- **Design Completion Time:** Traditional tools required an average of 35 minutes for a single layout creation, while the proposed system generated optimized layouts within 3 minutes including ML computation and rendering. This represents a reduction of nearly 90
- **Layout Consistency:** Manual designs exhibited higher variation in object spacing and alignment. The ML-driven system maintained uniformity with less than 5
- **Visual Realism:** The combination of dynamic lighting and realistic textures in Unity significantly improved depth perception compared to static 3D renders. User evaluation rated the visual realism of VR-based scenes 4.7/5 on average, compared to 3.9/5 for conventional 3D visualization.

These comparisons demonstrate that the proposed VR–ML hybrid model is not only computationally efficient but also enhances the subjective design experience and outcome quality.

### C. User Study

A user evaluation study was conducted to assess the effectiveness and usability of the VR-based design system. Ten participants were selected for testing, including architecture students, professional interior designers, and general users with limited design experience. Each participant was tasked with designing a living room layout using both traditional 3D software and the proposed intelligent VR system.

Feedback was collected through a structured questionnaire covering usability, realism, comfort, and recommendation relevance. Key outcomes of the user study are summarized below:

- 87
- 80
- 100

In addition, participants mentioned that the immersive environment allowed for better visualization of lighting, object arrangement, and color harmony, aspects often missed in non-VR tools. Users also appreciated the real-time reconfiguration feature, where

modifications made within the VR space triggered instant re-evaluation and adjustment by the ML engine. The System Usability Scale (SUS) score averaged 88.2/100, placing the interface within the “excellent” usability category. Participants with no prior design experience reported that the system reduced their cognitive load by automatically generating intelligent design suggestions, thereby allowing them to focus on creative decisions rather than manual adjustments.

#### **D. Discussion of Findings**

The findings validate that integrating machine learning with virtual reality significantly enhances both the functional and experiential aspects of digital design. The model successfully combines data-driven intelligence with immersive visualization, leading to measurable improvements in efficiency and user engagement.

One notable observation was that ML-generated layouts exhibited subtle design tendencies that aligned with aesthetic principles—such as balanced object distribution and consistent spacing—indicating that the model effectively learned implicit human design rules from the training data. Moreover, as users interacted with the VR environment, their behaviors (e.g., object movement or viewing duration) provided valuable feedback for iterative model improvement.

From a system-level perspective, maintaining near-constant frame rates under heavy computational loads proves that the proposed architecture is technically scalable. It can be extended to larger or more complex environments with minimal performance degradation by employing cloud-based ML inference or distributed rendering engines.

The successful outcomes of the user study, coupled with strong quantitative metrics, demonstrate that this system can serve as a practical bridge between computational intelligence and human creativity in real-world architectural design scenarios.

#### **E. Summary**

Overall, the experimental results confirm that the proposed Smart VR-Integrated 3D Visualization System performs efficiently across all major dimensions — speed, accuracy, usability, and scalability. The combination of real-time ML recommendations and immersive VR visualization offers a transformative experience, improving both design productivity and spatial understanding.

## VI. APPLICATIONS

The proposed Smart VR-Integrated 3D Visualization System has broad applicability across multiple domains that rely on spatial design, visualization, and interactive engagement. By combining immersive Virtual Reality (VR) with intelligent Machine Learning (ML)-based layout generation, the system addresses not only traditional design workflows but also emerging applications in real estate, education, retail, and digital commerce. The following subsections highlight some of the most promising areas where this system can be effectively deployed.

### A. Interior Design Visualization and Client Approval

One of the most direct and impactful applications of this system lies in the field of interior design visualization. Traditional design approval processes often involve multiple rounds of revisions between clients and designers due to differences in spatial perception or design expectations. Clients typically rely on 2D floor plans or static 3D renders, which fail to fully convey depth, proportion, and scale. This communication gap often leads to costly redesigns and time delays.

The proposed system solves this challenge by offering real-time, immersive VR walkthroughs of proposed layouts. Clients can virtually enter the designed environment, explore each corner of the space, and evaluate the arrangement, lighting, and aesthetics from a first-person perspective. Meanwhile, the integrated ML model can automatically adjust furniture placement or decor elements based on ergonomic and aesthetic principles, providing intelligent suggestions that align with both designer intent and client preferences.

For design firms, this drastically reduces approval turnaround time. Instead of manually editing designs based on client feedback, designers can make adjustments within the VR space itself, and the ML engine immediately re-optimizes the configuration. This capability shortens project cycles, minimizes design fatigue, and enhances overall client satisfaction.

### B. Real Estate Virtual Tours and Property Showcasing

In the real estate sector, VR has already proven to be an effective marketing and visualization tool. However, existing virtual tour systems are largely static and limited to pre-rendered environments. The Smart VR-Integrated system enhances this experience by introducing interactive and personalized property visualization powered by machine learning. Potential buyers can visualize unfurnished spaces with automatically generated interior layouts suited to their style preferences — for instance, modern, Scandinavian, or

tra- ditional — directly within the VR environment. The ML engine dynamically arranges furniture, lighting, and decorative elements, allowing the user to experience a fully furnished version of the property in real time.

Moreover, developers and real estate agents can use the system to generate multiple layout variations instantly, show- casing different spatial configurations or furnishing packages. This flexibility provides a powerful marketing advantage, enabling buyers to make faster and more confident purchase decisions. The immersive walkthrough also allows investors or remote clients to inspect properties without physical visits, thereby reducing logistical costs and expanding outreach to global audiences.

### **C. VR-Based Architectural**

Training and Education Architectural education is increasingly adopting technology-enhanced learning tools to train students in spatial reasoning, structural design, and environmental awareness. The proposed VR–ML system serves as an advanced educational platform where students can not only visualize architectural concepts but also interact with them dynamically.

Students can import floor plans, generate automated 3D layouts, and enter the virtual environment to evaluate scale, lighting, and ergonomics. The ML engine assists by suggesting optimized arrangements or highlighting design inefficiencies, thereby serving as an intelligent tutor that reinforces design principles through data-driven analysis.

Moreover, the system promotes experiential learning — students learn by doing. They can test hypothetical scenarios, such as altering furniture size, changing room dimensions, or adjusting lighting intensity, and immediately observe the resulting spatial impact in VR. This immediate feedback loop enhances spatial cognition, making abstract design concepts tangible and intuitive. As a result, architectural and interior design programs can integrate this system into studio courses, workshops, or collaborative design sessions.

### **D. AI-Driven Layout Tools for Furniture E-Commerce**

The e-commerce industry, particularly in furniture and home decor, is another domain that stands to benefit from this sys- tem. Online shopping platforms often face high product return rates due to customers' inability to visualize how products will look or fit within their actual spaces. By integrating the Smart VR–ML system into e-commerce websites, users can virtually furnish a 3D model of their home using selected products and visualize them in immersive VR before purchase.

The ML engine can recommend furniture sets based on user behavior, room size, and existing decor preferences — functioning as an AI-driven recommendation system for spatial design. For example, if a customer selects a minimalist sofa, the system can automatically suggest complementary coffee tables, lighting fixtures, and wall colors that match the overall aesthetic and dimensions of the room. This not only improves the shopping experience but also boosts customer confidence and reduces post-purchase dissatisfaction.

Retailers can also leverage the analytics generated by the system. By studying how users interact with products in VR — such as which items they move, resize, or discard — retailers can gain valuable insights into consumer behavior and trends. This data can inform inventory management, product development, and targeted marketing strategies.

### **E. Smart City Planning and Urban Visualization (Emerging Application)**

Beyond interior design and real estate, the system’s underlying architecture can be scaled up for urban and smart city planning. By extending the ML models to handle larger datasets and integrating Geographic Information System (GIS) data, city planners can simulate urban layouts, traffic flow, and environmental impact in immersive VR environments. This helps decision-makers evaluate infrastructure projects, zoning regulations, and public space utilization in a more interactive and data-driven manner.

For example, VR visualizations can allow stakeholders to “walk through” future city developments, while ML algorithms analyze accessibility, crowd density, or environmental sustainability metrics. This combination of immersive visualization and computational analysis fosters better-informed decisions and more efficient planning outcomes.

### **F. Summary**

The versatility of the Smart VR-Integrated 3D Visualization System extends far beyond a single industry. Its modular structure enables adaptation to multiple contexts where spatial analysis, visualization, and design optimization are required. Whether for professional design studios, real estate developers, e-commerce retailers, or academic institutions, the system delivers value by transforming abstract data into intuitive, immersive, and intelligent experiences.

By merging VR’s capability to represent physical space with ML’s ability to learn from and optimize that space, this technology redefines how users design, explore, and interact with their environments — paving the way for a new era of smart, data-driven spatial computing.

## VII. LIMITATIONS

Despite the promising outcomes of the proposed Smart VR- Integrated 3D Visualization System, several limitations and technical constraints were observed during the development and testing phases. These challenges primarily arise from hardware requirements, dataset characteristics, and user-device variability. Understanding these limitations is essential for identifying future areas of improvement and guiding subsequent iterations of the system.

### A. High GPU Dependency for Real-Time Rendering

One of the most significant limitations of the system lies in its heavy dependency on high-performance graphics processing units (GPUs) for real-time rendering and smooth VR performance. The proposed framework involves rendering complex 3D environments with dynamic lighting, texture mapping, and physics simulations. Each of these tasks demands substantial graphical processing power to maintain a stable frame rate above 50–60 FPS, which is necessary to prevent user discomfort or motion sickness during immersive sessions. Testing indicated that the system performs optimally only on mid-to-high-end hardware configurations such as NVIDIA RTX 2060 or above. On lower-end GPUs, frame drops and rendering delays were observed, particularly when the scene contained multiple reflective surfaces, shadows, or detailed assets. These performance bottlenecks directly affect the realism and responsiveness of the VR environment, reducing the overall quality of user experience.

Additionally, as the ML engine operates concurrently with the Unity rendering process, the combined computational load further increases GPU usage. Even though certain optimizations such as occlusion culling and LOD (Level of Detail) management were implemented, the system still relies on significant GPU memory bandwidth to maintain performance stability. This limits accessibility for smaller organizations or educational institutions that may lack high-end computing infrastructure.

Mitigation Strategies: Future work could explore cloud-based rendering solutions such as NVIDIA CloudXR or Amazon Sumerian to offload heavy processing tasks from local hardware to cloud servers. This approach would enable real-time streaming of rendered VR content to lightweight devices, making the system more scalable and affordable. Additionally, techniques like foveated rendering—which reduces graphical detail in the user’s peripheral vision—can be implemented to optimize GPU usage without compromising perceived visual quality.

## B. Limited Dataset Diversity Affecting Generalization

The performance of the ML layout prediction model largely depends on the diversity and quality of the training dataset. In the current implementation, the dataset comprises a combination of public datasets (MIT Scene Layout and SUN RGB-D) and 500 custom-generated synthetic layouts. While this provides a solid foundation for learning spatial relationships and ergonomic principles, it still falls short in covering the full spectrum of global interior design variations.

Many factors such as regional architectural styles, cultural aesthetics, lighting preferences, and furniture typologies vary significantly across geographical locations. Since the dataset used for training was biased toward modern and minimalist designs, the system occasionally produces less accurate or stylistically inconsistent results when applied to other design paradigms such as traditional, industrial, or bohemian interiors.

Moreover, real-world interior data often contains noise—occlusions, incomplete annotations, or inconsistencies in object scaling—that can degrade model accuracy. Although the system achieved a high average prediction accuracy (91.4%), Mitigation Strategies: To enhance generalization, future iterations of the system should incorporate a larger and more diverse dataset. Crowdsourcing annotated layout data from global design repositories or integrating publicly available datasets such as Matterport3D or Replica could help achieve better diversity. Transfer learning approaches can also be applied to fine-tune the model for region-specific design preferences. Moreover, active learning pipelines—where user corrections during VR interactions are fed back into the training dataset—can enable the model to continuously evolve based on real-world use cases.

## C. Potential Motion Lag on Low-End or Untethered Devices

Virtual Reality applications are highly sensitive to latency. Any delay between user movement and corresponding visual updates can cause disorientation or motion sickness. Although the system maintained smooth performance on high-end hardware, some latency and motion lag were observed when tested on standalone VR devices such as the Oculus Quest (untethered mode) and lower-spec PCs.

This lag primarily stems from synchronization delays between the Unity rendering engine and the ML inference module. Because the ML model performs layout optimization in near real-time, any delay in the prediction response can temporarily interrupt the flow of interaction. Additionally, hardware limitations on mobile or untethered devices restrict the

complexity of rendered environments due to memory and processor constraints.

Another contributing factor is network latency when using cloud-based rendering or remote ML inference. Even minor transmission delays can accumulate, resulting in noticeable lag during interactive design modifications. In highly immersive environments, even a 100–200 ms latency can disrupt user experience.

**Mitigation Strategies:** Future improvements could involve deploying a lightweight ML inference model optimized with TensorFlow Lite or ONNX Runtime to reduce latency during layout computation. Caching precomputed layouts and using asynchronous rendering techniques can also mitigate lag. For standalone devices, hybrid rendering approaches—where low-complexity assets are rendered locally and high-fidelity textures are streamed dynamically—may strike an optimal balance between performance and realism.

Furthermore, implementing predictive tracking algorithms can compensate for minor motion delays by estimating user head and hand movement trajectories ahead of actual rendering frames.

#### **D. Other Observed Limitations**

In addition to the primary constraints discussed, several secondary limitations were noted during evaluation:

**Lighting Adaptation:** The system’s lighting model currently lacks dynamic exposure adjustment. Overexposed or underlit regions occasionally appear in reflective surfaces, affecting realism.

**User Personalization:** While the ML model accounts for ergonomic and aesthetic rules, it does not yet adapt fully to individual user behavior or personal preferences beyond style templates.

**Data Security:** Storing user interaction logs and design data introduces privacy concerns that need to be addressed through secure encryption and anonymization mechanisms.

#### **E. Summary**

Overall, the limitations identified do not undermine the system’s core functionality but rather highlight opportunities for refinement. The dependency on high-end GPUs, limited dataset generalization, and minor latency issues are expected challenges in the development of complex VR–ML hybrid frameworks. Addressing these issues through cloud integration, active learning, and hardware optimization will significantly enhance accessibility, robustness, and adaptability of future iterations of the system.

## VIII. CONCLUSION AND FUTURE WORK

The research presented in this paper demonstrates that the integration of Virtual Reality (VR) and Machine Learning (ML) within a unified computational framework can substantially enhance both the efficiency and quality of spatial design visualization. The proposed Smart VR-Integrated 3D Visualization System addresses fundamental limitations in traditional design workflows by combining immersive visualization with intelligent, data-driven design assistance. Through this hybrid approach, the system transforms the way designers, clients, and stakeholders perceive and interact with architectural spaces.

The experimental evaluation confirms that the framework achieves high accuracy, responsiveness, and user satisfaction. The system consistently maintained rendering frame rates between 55–60 FPS, ensuring smooth and realistic immersive experiences. The ML component achieved a prediction accuracy of 91.4

From a technical standpoint, the system's modular architecture—comprising the Input Asset Manager, Machine Learning Engine, 3D Rendering Module, VR Visualization Module, and Database Layer—ensures scalability, maintainability, and flexibility for diverse design applications. The hybrid ML model, utilizing K-Means clustering for spatial zoning and neural networks for coordinate prediction, successfully captured complex spatial relationships while maintaining computational efficiency. The integration with Unity 3D and OpenXR SDK enabled real-time rendering and multi-device compatibility, making the system accessible across various VR hardware platforms.

Beyond technical performance, the proposed system introduces a new dimension of human-centered design intelligence. By allowing users to engage interactively with their designs, the system bridges the gap between computational automation and creative exploration. Unlike conventional computer-aided design (CAD) tools, which rely on static modeling, the Smart VR-Integrated framework actively learns from user interactions—adjusting recommendations, refining spatial predictions, and improving aesthetic coherence over time. This iterative feedback loop positions the system as a continuously evolving design companion rather than a static visualization tool.

The results collectively indicate that this convergence of VR and ML marks a significant step forward in the evolution of digital design technologies. Designers gain access to intelligent automation that reduces manual effort and time spent on iterative modeling, while clients benefit from immersive, realistic previews that simplify decision-making. The combination of predictive intelligence and immersive engagement ultimately leads to higher-quality outcomes, reduced design cycles, and improved collaboration between stakeholders.

### A. Key Contributions

The major contributions of this research can be summarized as follows:

**A Unified Framework:** Development of an integrated VR–ML architecture that bridges visualization, interaction, and predictive analytics for spatial design automation.

**Intelligent Layout Optimization:** Implementation of a hybrid ML model combining clustering and neural prediction to generate context-aware, ergonomic, and visually balanced layouts.

**Immersive Interaction:** Seamless coupling of Unity 3D’s rendering pipeline with TensorFlow’s inference engine for real-time immersive visualization.

**Data-Driven Evaluation:** Empirical validation of system performance across key metrics such as frame rate, latency, prediction accuracy, and user satisfaction.

**Adaptable Design System:** Creation of a modular platform capable of continuous learning from user behavior and feedback, allowing adaptive system evolution over time.

These contributions not only demonstrate technical feasibility but also establish a foundation for future exploration in intelligent and immersive design technologies.

### B. Limitations and Research Implications

While the system performs well in experimental settings, certain limitations were identified that pave the way for future research. The reliance on high-end GPUs limits accessibility on low-resource hardware. The dataset used, though comprehensive, lacks global diversity and may not generalize across cultural or stylistic variations. Additionally, motion lag on standalone VR devices and network latency in cloud configurations require further optimization.

These constraints suggest broader research opportunities in distributed rendering, cloud-based ML inference, and federated learning, where multiple clients can contribute anonymized data to a central model for collective improvement. Furthermore, exploring domain adaptation techniques could help extend the system’s predictive capabilities to new design styles or environments without requiring complete retraining.

### C. Future Work

Building upon the foundation established in this work, several promising directions for enhancement and future research are envisioned:

**Integration of Augmented Reality (AR) Overlays:** Future versions of the system will incorporate AR functionality to merge physical and virtual design experiences. Users could

view ML-optimized layouts projected directly onto their real environments through AR headsets or mobile devices, enabling seamless comparison between virtual designs and physical spaces.

**Expansion of Datasets with Generative Models:** Leveraging Generative Adversarial Networks (GANs) or Variational Autoencoders (VAEs) could allow the system to generate synthetic yet realistic layouts that expand the dataset beyond manually curated samples. This would improve generalization and reduce data scarcity issues in underrepresented design styles.

**Cloud-Based Collaborative Design Tools:** The development of a cloud-based infrastructure would facilitate multi-user collaboration in shared virtual environments. Multiple designers and clients could interact in real time, annotate layouts, and co-create designs. Cloud rendering would also eliminate hardware limitations by offloading intensive computations to remote servers.

**Personalization Through Reinforcement Learning:** Integrating reinforcement learning mechanisms would enable the system to adapt more precisely to individual user preferences. By learning from repeated interactions, the system could refine its recommendation policies to align with each user's design tendencies, ultimately delivering a personalized design assistant experience.

**Cross-Platform Accessibility and Mobile Optimization:** Expanding support for standalone and mobile VR devices such as Oculus Quest and Pico headsets would make the technology more accessible. Lightweight ML models and adaptive rendering algorithms will be essential for ensuring smooth performance on such devices.

**Sustainability and Smart Building Integration:** Future iterations may integrate energy-efficiency models and sustainability metrics, allowing designers to evaluate environmental impacts such as lighting efficiency or material waste. This aligns the system with broader smart building and sustainable design initiatives.

#### **D. Final Remarks**

In conclusion, this research demonstrates that the synergy between Virtual Reality and Machine Learning is not merely additive but transformative. By unifying immersive visualization and predictive intelligence, the Smart VR-Integrated 3D Visualization System establishes a new paradigm in digital design automation. It empowers designers to visualize, analyze, and optimize spatial layouts more intuitively and efficiently than ever before.

As the boundaries between physical and digital environments continue to blur, systems like

the one presented here will play a critical role in shaping the future of spatial computing, smart cities, and human-machine collaboration.

The integration of VR and ML thus stands as a cornerstone for next-generation design ecosystems — intelligent, adaptive, and profoundly human-centered.

## IX. ACKNOWLEDGMENT

The authors sincerely express their gratitude to Prof. S. S. Nimase, Department of Computer Engineering, Shri Chha- trapati Shivaji Maharaj College of Engineering, Ahilyanagar, for his continuous guidance, encouragement, and technical insights throughout the course of this research. His mentorship played a vital role in refining the methodology, experimental design, and interpretation of the results presented in this work. The authors would also like to thank the faculty and laboratory staff of the Computer Engineering Department for providing the necessary infrastructure, resources, and technical support for the implementation and testing of the proposed system.

Special appreciation is extended to the peer reviewers and fellow students whose valuable feedback during prototype evaluations contributed to improving system performance and usability. Their constructive suggestions greatly enhanced the quality and clarity of the final design.

Lastly, the authors acknowledge the open-source commu- nities behind TensorFlow, Unity 3D, and OpenXR SDK, whose publicly available tools and documentation facilitated the seamless integration of machine learning and virtual reality technologies in this project.

This work reflects a collaborative effort combining technical innovation, academic mentorship, and institutional support toward advancing intelligent visualization systems in spatial computing and design automation.

## REFERENCES

1. Molla, A., Sharma, D., Patel, R., “Immersive Visualization Techniques for Real Estate Walkthroughs,” *IEEE Access*, vol. 9, pp. 45120–45132, 2021.
2. Zhao, J., Li, W., “Spatial Layout Optimization using Machine Learn- ing,” *Journal of Design Computing*, vol. 14, no. 2, pp. 115–128, 2022.
3. Reddy, S., Patel, D., “AI-Powered Interior Design using Deep Neural Models,” *Procedia Computer Science*, vol. 182, pp. 301–310, 2020.
4. Lee, T., Kim, J., “Reinforcement Learning for Intelligent Layout Design,” *Proceedings of the ACM VRIC*, pp. 245–252, 2022.

5. Singh, P., Mehta, R., “GAN-based Automated Interior Decoration Framework,” IEEE Transactions on Visualization and Computer Graphics (TVCG), vol. 29, no. 4, pp. 1415–1427, 2023.
6. Amin, J., Sharif, M., Qureshi, A., “Smart Visualization and ML-based Design Frameworks,” IEEE Transactions on Emerging Technologies in Computing, vol. 12, pp. 1–10, 2021.
7. Kumar, P., “Real-time VR Systems with Predictive Intelligence,” Proceedings of the ACM VRIC Conference, pp. 87–94, 2023.
8. Chen, M., Xu, L., Zhang, H., “Hybrid Neural Design Assistants for Architecture,” Automation in Construction, Elsevier, vol. 141, pp. 104512, 2022.
9. Li, F., Wang, J., “Interactive VR Systems for Spatial Planning and Visualization,” IEEE Transactions on Visualization and Computer Graphics, vol. 26, no. 10, pp. 3198–3210, 2020.
10. Panwar, S., Das, R., Gupta, P., “Generative Layout Systems with Machine Learning: A Multi-modal Framework,” Proceedings of the International Conference on Intelligent Computing (ICIC), pp. 523–534, 2024.
11. Huang, X., Chen, Y., “Collaborative VR Platforms for Architecture and Interior Co-design,” International Journal of Human–Computer Interaction, vol. 37, no. 7, pp. 662–674, 2021.
12. Patel, N., Deshmukh, S., “Integrating Artificial Intelligence with Virtual Reality for Smart Building Design,” Elsevier Journal of Intelligent Environments, vol. 45, no. 3, pp. 231–244, 2023.
13. Luo, K., “Deep Learning for Spatial Understanding in Virtual Environments,” IEEE Transactions on Neural Networks and Learning Systems, vol. 33, no. 9, pp. 4201–4212, 2022.
14. Ghosh, A., Banerjee, T., “Data-driven VR Simulation Framework for Real-time Architecture Evaluation,” Computers and Graphics, Elsevier, vol. 108, pp. 72–85, 2024.
15. Lin, S., Wu, Q., “Generative AI and XR: Next-Generation Design Paradigms,” IEEE Spectrum, vol. 60, no. 6, pp. 54–61, 2023.